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A CRITICAL REVIEW OF THE CHANGE DETECTION AND URBAN CLASSIFICATION LITERATURE

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Prepared for

GODDARD SPACE FLIGHT CENTER

By

COMPUTER SCIENCES CORPORATION

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ABSTRACT

Selected literature in the area of change detection using remote sensing is reviewed. The principles behind the methods of image differencing, image rationing, principal components, analysis of residuals, and discriminant analysis are discussed and their use and misuse, in the literature reviewed, is examined. Other miscellaneous methods are mentioned briefly. Several recommendations for future studies are proposed.

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SECTION 1 - INTRODUCTION

The Bureau of the Census is charged with providing information on the demographic status of the nation for use by the Department of Commerce and other branches of the Government. Because the rate of demographic change has increased and the distribution of Federal funds is frequently based on demographic criteria, the need has arisen for the Census Bureau to update its data more frequently. Public Law 94-521, signed into law as of October 1976, requires a mid-decade census. To minimize the cost of obtaining data over the shorter 5-year time intervals, the Census Bureau has been investigating what it hopes will be more economical methods of data collection. One of many potential methods is the use of satellite remote sensing to detect large-scale land cover changes that may be associated with the expansion of urban areas.

The Census Bureau defines urban areas for each of the nation's standard metropolitan statistical areas as contiguous areas with a minimum density of 1000 per square mile (Christenson, et al., 1977; Reference 1). After each census, the Census Bureau defines an official urban boundary based on its data. The Bureau also established a second boundary outside the official urban boundary. The area enclosed by these boundaries is called the "urban fringe zone." The urban fringe zone is the area where urban growth is expected during the interval to the next census (Christenson and Lackowski, 1976; Reference 2).

Because the data used by the Census Bureau is imperfect, the official urban boundary, a line drawn on a map by Census Bureau personnel after each census is not necessarily coincident with the true urban boundary determined by the true contiguity and density properties of the area. This distinction between the official and the true urban boundary should be kept in mind while reading the following.

The demarcation of urban boundaries is an important demographic factor in the allocation of Federal funds. Because these boundaries can change rapidly

relative to the decennial census, the Census Bureau and the National Aeronautics and Space Administration (NASA) have chosen to study the ability of satellite remote sensing to detect change in urban boundaries.

In preparation for this study, a preliminary critical review of the unclassified literature on change detection and urban scene analysis was conducted. This report is the result of that review.

This report mainly concerns the methods of detecting and classifying change between two satellite images taken at different dates that have already been registered to each other or registered to a ground coordinate system. Thus, change detection can be considered a two-step sequential process: (1) the detection of change and (2) the classification of the change detected. Because the previous official (as opposed to the actual) urban boundaries were determined by the Census Bureau in the traditional manner, only the changes, usually extensions, of the boundaries need to be detected. In using remote sensing, it is hoped that the changes between the old date and the new date land cover will be reflected by changes in the corresponding images. Preliminary studies (Stauffer and McKinney, 1978; Reference 3), indicate that changes in the Landsat images can be related to changes in urban boundaries.

Three methods for detecting changes between images recorded on two different dates are: differencing of the registered images, ratioing of the registered images, and analysis of the residuals after regressing one image on the other. A fourth method is to combine images from different dates to form multitemporal images and then classify them with standard analysis methods or using a layered spectral/temporal change classification method (Weismiller et al., 1977; Reference 4). Each of these methods, together with examples of its application, is discussed in turn. After discussing these methods, a study using a fifth, less familiar, approach in which ancillary geologic and geographic information is used for detecting and classifying change, is discussed.

Identifying those picture elements (pixels) that have changed over the time interval is only the first step. The second step is to determine the type of landcover change that is reflected by the changed pixels. This second step can itself be broken into two parts. The type of landcover change can be divided into two basic types: changes of interest (i.e., from nonurban to urban or from one urban type to another urban type) and changes that are not of interest, (i.e., changes in crop type for agricultural land). Because of the effects of the ever-growing population, urban types essentially never become nonurban; however, if the demographic trends changed, this type of change would be of interest. Classification of the changes of interest is the last step in the process.

SECTION 2 - CHANGE DETECTION ALGORITHMS

2.1 DIFFERENCING

One of the simplest ways of looking for change pixels is to difference the registered images from the two dates of interest. If no change has occurred and $P_{0_{ij}}^{(k)}$ is the value of the jth pixel from the ith row from the old date for band k and $P_{1_{ij}}^{(k)}$ is the jth pixel from the ith row from the new date for band k, then $P_{d_{ij}}^{(k)}$, the jth difference pixel from the ith row for band k, has an expected value of 0:

$$\mathcal{E}\left(P_{d_{ij}}^{(k)}\right) = \mathcal{E}\left(P_{0_{ij}}^{(k)} - P_{1_{ij}}^{(k)}\right) = 0 \qquad (2\text{-}1)$$

To minimize the effect of seasonal variation, anniversary dates are usually chosen for differencing. This is also true for the ratioing and regression methods discussed below.

Angelici et al. (1977; Reference 5) used two approaches for detecting change by differencing. These approaches, which can be used with either raw or transformed data, were the difference-delimit method and the delimit-difference method. In the first method, the two registered images are differenced and the resultant image is delimited using histogram thresholding techniques.

Thresholding is the process of setting bounds about intervals of the variables (bands) based on the shape of each variable's histogram. All pixels to fall within the interval are delimited on the image because their values fall within the upper and lower thresholds set on the variables.

In the second method, each registered image has its histogram thresholded to delimit urban from nonurban areas. The two classified images are then differenced to find the changed areas. As Angelici et al. did not present information on the success rate of each method, no information is available to evaluate the degree of success of either method for the task at hand.

Instead of the raw MSS band images, Angelici et al. used two different transformations. One transformation was the ratio of band 5 to band 7 for each image. For the other transformation, the second principal component from each date was used.

The use of ratios may provide empirically acceptable results but their distributions are usually not normal (non-Gaussian). Sometimes this non-normality can be treated with the proper transformation of the ratio. Angelici et al. did not deal with this problem except to apply a Gaussian stretch to "normalize" the distribution after the MSS5/MSS7 had been differenced. The problem with the Gaussian stretch is its ad hoc nature. It would be more desirable to use a standard transformation such as an arc sine ($\sin^{-1}(\sqrt{P})$) transformation (Sokal and Rohlf, 1969; Reference 6). If the standard transformation passes the necessary normality tests, it can be used with subsequent data sets.

Principal components, which is the second transformation used by Angelici et al., involves rotating the coordinate axes so that the first axis maximizes the variance, the second axis maximizes the residual variance and is orthogonal to the first, the third axis maximizes the residual variance orthogonal to the first and second axes, and similarly for the fourth, fifth, etc. In matrix algebra terms, the following relations hold for principal components analysis.

Raw data matrix $X_{p \times n}$ with p variables and n observations with zero mean and distributed as $N(x \mid 0 \mid \Sigma)$ has a p-by-p matrix, $A_{p \times p}$, of eigenvectors such that $Y_{p \times n}$, the matrix of principal components, is equal to the premultiplication of $X_{p \times n}$ by $A_{p \times p}$:

$$Y_{p \times n} = A_{p \times p} \cdot X_{p \times n} \tag{2-2}$$

The sample sums of squares and cross-products matrix, $S_{p\times p}$, equals

$$X_{p\times n} \cdot X'_{n\times p} \qquad S_{p\times p} \sim W(S|n-1|\Sigma) \tag{2-3}$$

$$L_{p\times p} = Y_{p\times n} \cdot Y'_{n\times p} \qquad L_{p\times p} \sim W(L|n-1|\Lambda) \tag{2-4}$$

$$L_{p\times p} = A_{p\times p} X_{p\times n} \cdot X'_{n\times p} A'_{p\times p} \tag{2-5}$$

where $L_{p\times p}$ is the diagonal matrix of eigenvalues; the eigenvalues are the sums of squares of the orthogonal transformed data set, $Y_{p\times n}$; Σ is the parametric variance-covariance matrix of the population from which the sample X is drawn; Λ is the parametric matrix of eigenvalues; n is the number of observations; and p is the number of variables with $n >> p$. $N(X|0|\Sigma)$ is a normal distribution with a parametric mean of zero and a variance-covariance matrix of Σ. $W(S|n-1|\Sigma)$ is a Wishart distribution with n-1 degrees of freedom and variance-covariance matrix Σ, or Λ as in $W(L|n-1|\Lambda)$.

Principal components has been used when the parametric assumptions have not been met. However, usually this has been for descriptive studies, particularly in the social sciences; and biology (e.g., Cooley and Lohnes, 1971; Reference 7; Sokal and Sneath, 1963; Reference 8). In these cases, no significance testing was carried out and the technique was used for dimensionality reduction in an empirical fashion. However, empirical use of the technique does not justify ignoring the analytic and geometric foundation on which principal components analysis is based.

Angelici et al. calculate the principal components separately for each date's data set (see their flowcharts in Reference 5, Figure 5(a) and (b)). This assumes that the underlying Σ for each data set are the same. (It should be noted that the eigenvectors of Σ and of $c\Sigma$, where c is a constant, are the same but

if $\Sigma_1 \neq c\Sigma_2$ the eigenvectors of Σ_1 are not equal to the eigenvectors of Σ_2.) They should have tested the equality of the Σ's by using Bartlett's test on the sample variance-covariance matrices. If no significant difference was found, the two sample variance-covariance matrices could be combined in the usual manner (Kshirsager, 1972; Reference 9, pages 143-44) and the principal components calculated from this pooled estimate.

If the original axes are considered the reference basis and the variance-covariance matrices are not equal, the method used by Angelici et al. would be equivalent to differencing two different variables instead of the intended two different values of the same variable. In this case, any favorable empirical result would be fortuitous. Because Angelici et al. neither tested the homoscedasticity of the variance-covariance matrices nor gave the accuracy of the various methods they used, it is not possible to evaluate the performance of their methods.

In their principal components transformation, they used the second principal component. They did not explain why they chose the second principal component instead of the first, which contains the largest proportion of the variance. According to Stauffer (personal communication), the rationale for this choice is that the first principal component is primarily influenced by the overall variation in scene brightness in all the bands whereas the other principal components contain contrasts between the bands and are more useful for classification.

In the analysis of a multidate (October 11, 1972, and April 9, 1973) 8-band Landsat image of Prince Georges County, Maryland, which is a mixed suburban-rural county adjacent to Washington, D.C., Williams and Borden (1977; Reference 10) indeed found that the first principal component acted like a "size factor" in morphometric studies (Seal, 1964; Reference 11). The first principal component contained 59.4 percent of the variation, the second 24.3 percent, the third 10.5 percent and the fourth 4.0 percent (Williams and Borden, 1977;

Reference 10). Unlike Angelici et al., they used the first five out of eight possible principal components to classify their pixels into urban, nonurban categories using Euclidian distance classifiers. Angelici et al. used only the second principal component. Williams and Borden claimed that their classifier worked better with the principal component than with the untransformed data. Angelici et al. did not make a comparison.

Podwysocki et al. (1977) (Reference 12) reported 94 percent of the total variation in the first component and 4.5 percent in the second in their analysis of Landsat (4-band) data from the Utah desert area known as the "Waterpocket Fold." This would suggest that some of the variation in the first principal component would be useful for discrimination. Using the discriminant functions used by Podwysocki et al. (provided by Gunther), the cosines between the discriminant functions and the eigenvectors for the Waterpocket Fold were calcaluated as shown below.

	DF1	DF2
EV1	0.505	0.024
EV2	-0.437	0.562

This shows that at least with their data, a portion of the variance explained by the first principal component would also be useful for discriminating between the classes of interest.

Blodget et al. (1978; Reference 13), in a similar study of southwestern Saudi Arabia, had 96.46 percent in the first eigenvalue, 1.85 percent in the second, and 1.04 percent in the third eigenvalue. In their canonical analysis, 94.38 percent of the between-group variance adjusted for within variance were in the first axis, 4.85 percent in the second, and 0.67 percent in the third. The cosines between the first two disciminant functions and eigenvectors are given below.

	DF1	DF2
EV1	0.961	0.095
EV2	-0.010	0.767

It is clear that the first discriminant axis is nearly coincident with the first principal component. This indicates that dropping the information in the first principal component quite likely decreased the ability of Angelici et al. to discriminate between urban and nonurban pixels.

In their application of the difference-delimit method, Angelici et al. first classified points beyond two standard deviations as change. They then decided this was an excessive amount and classified points beyond three standard deviations as change. Both of these cutoff points were subjective choices and were not compared with ground truth in their paper.

Weismiller et al. (1977; Reference 4) also used image differencing as one method in their comparison of four change detection algorithms. The utility of their comparison is compromised by the lack of ground truth. They had only aerial photographs for the second date.

Weismiller et al. used the postclassification comparison change detection as their standard against which they compared the other three methods. In the postclassification comparison change detection method, both the first and second dates are classified independently. The classifications for each date are compared to develop a change image.

In addition to differencing, they used the spectral/temporal change classification and a layered spectral/temporal approach. In both of these methods, a multitemporal image is formed by images from the combined first and second dates. The former method involves using "standard pattern recognition techniques" (Weismiller et al., 1977; Reference 4) on the multitemporal data set. In the latter method, a decision tree is followed using selected channels in the

multidate image as input to decision functions. A decision function exists at each node in the decision tree.

They concluded that information was lost in the differencing procedure but failed to specify the mechanism or type of information loss. The problem with the layered decision tree is the large amount of computing resources required. In addition, the nature of the decision function is quite likely locality dependent.

Anuta (1974) (Reference 14) used the difference method with registered, rectified data to produce a change image. He then used a clustering method to classify the difference pixels. He found that whereas all construction was correctly identified, other changes that were not construction, such as parking lots, gravel pits, industrial yards, and changes in agricultural areas, were also classified as construction. Stauffer and McKinney (1978; Reference 3) also reported some confusion of other types (extractive and agricultural) with construction.

Riordan (1979; Reference 15) has pointed out some of the general difficulties in differencing. Examples are the sensitivity to misregistration and the existence of mixed pixels (termed "mixels" by Riordan). She also points out the necessity of distinguishing between the changes of interest (nonurban to urban), and those not of interest (nonurban to nonurban).

Image differencing has been used with a variety of transformed and untransformed data. If proper attention is paid to the technical problems of image registration and the distributions of the transformed or untransformed data, further progress might be possible with this technique. It is clear that better methods of distinguishing between significant and nonsignificant change must be developed. Furthermore, significant change must be "partitionable" into its component categories so that changes that are of interest can be distinguished from those that are not interesting.

2.2 RATIOING

In ratioing, two registered images from different dates with one or more bands in an image are ratioed band by band. Using the notation of Equation (2-1), the expected value is

$$1 = \mathcal{E}\left(P_{r_{ij}}\right) = \mathcal{E}\left(P_{0_{ij}} / P_{1_{ij}}\right) \tag{2-6}$$

Significant deviations from 1 can be considered change. The problem with ratios is that the distributions are far from normal and various transformations are required to cause them to approach normality. If the distributions are distinctly nonnormal and functions of the standard deviation are used to delimit change from nonchange, the areas delimited on either side of the mode are not equal. Therefore, the error rates on either side of the mode are not equal.

Todd (1977; Reference 16) used the ratio technique to detect change over the 2-year period, 1972 through 1974, in 136 square kilometers around the Atlanta area. He ratioed Landsat Multispectral Scanner (MSS) five from the Landsat scene of the first date with MSS five from the second scene. Using the Image-100 processor, Todd classified the change pixels. Significantly, Todd states that all areas larger than 14 hectares in which land use or landcover changed over the 2-year period were correctly categorized as change using the Image-100. When all change polygons are considered, 91.4 percent of the total area that actually changed was classified as change and 78 percent of the polygons that changed were correctly identified as change polygons. With the Image-100, histograms of the image pixels can be partitioned interactively by inspection so that the skewed distributions generated by ratioing would not seriously interfere with the analysis; however, in an automated analysis using parametric methods, it would be a problem.

Todd's error rate for classifying change into its component types was considerably higher. Ten out of 19 single-family residence areas were correctly classified. However, for the combined class of commercial-industrial multi-family and cleared land, 53 out of 63 areas of change were correctly classified. Todd's test site had no change areas in the other three land use and landcover categories of forested, open space or water areas. This would suggest that the 53 out of 63 (84-percent) success rate for the combined change category is not as impressive as it first seems, as the categories with which it might have been confused were not present. Further studies of the ratioing method under a variety of conditions would be useful.

2.3 REGRESSION

In the regression method of change detection, pixels from one year are assumed to be a linear function of the other years' pixels. The model is

$$\mathcal{E}\left(P^{(k)}_{1_{ij}} - \left(b^{(k)}_1 P^{(k)}_{0_{ij}} + b^{(k)}_0\right)\right) = \mathcal{E}\left(r^{(k)}_{ij}\right) = 0 \qquad r^{(k)} \sim N(r \mid 0; \Sigma_e) \qquad (2\text{-}7)$$

The residuals are assumed to have zero mean and to be independent and normally distributed. In Equation (2-7), b_0, the intercept, corrects for the difference in mean value and b_1, the slope, provides a linear correction for the difference in the brightness range. In the past, image analysts have used compression or stretching of the contrast range and empirical mean shifting to match two images before ratioing or differencing them. The least-squares approach minimizes the error in the adjustment of the two images, therefore providing the optimal matching of the images. Murai (1976; Reference 17) compared ratioing, differencing, and regression, and stated that regression gave superior results in his study of urban change in Tokyo. However, as he gave few details of this comparison, further evaluation of his conclusion is not possible.

The regression model can be expanded to take into account other interfering variables such as rainfall. This flexibility in the regression model gives it greater power than the previously discussed methods.

SECTION 3 - PRIOR KNOWLEDGE AND THE CLASSIFICATION OF CHANGE

Work reported by Tom, Miller, and Christenson (1978; Reference 8) constitutes a preliminary effort to use prior knowledge of an area to identify and classify change in a temporal series of Landsat images. Because their paper has a number of expository and methodological flaws, it is discussed in some detail below.

Not only did they use suboptimal methods in their analysis; but furthermore, their description of discriminant analysis is inaccurate. They assert that discriminant analysis is a nonparametric method which (their authoritative references notwithstanding) is not correct. The BMD Biomedical Computer Programs manual (Dixon, 1968; Reference 19, p. 214i) that describes the algorithm used by Tom et al. mentions the normality assumptions required for tests of significance and accurate calculation of error rates. Lachenbruch (1975; Reference 20) discusses the pitfalls of using BMD07M (which was the algorithm used by Tom et al.) when parametric assumptions are not met. Furthermore, Tom et al. (1978) assert that discriminant analysis changes the multivariate problem into a univariate problem. This is only true if the means are colinear or there are only two groups (Lachenbruch, 1975; Reference 20; Kshirsager, 1972; Reference 9; Dempster, 1969; Reference 21). Tom et al, had 38 groups or classes and presented no evidence or tests of colinearity.

In an effort to test for the existence of a relationship between their landscape variables and the category of change experienced by those cells (the square cells are the smallest unit of area used in the study and are four hectares in size) that changed over the time interval, Tom et al. used a modified version of BMD07M to classify the cells that they knew had changed, using the landscape variables. There are two problems with their approach. If they were simply

to use landscape variables to predict the cell type after an interval, they neglected the fact that in practice the cells that have changed are not known in advance.

Limiting the test of the derived discriminant functions to those cells Tom et al. already knew had changed gave a more favorable result than would have occurred with a random sampling of cells. Also, had they instead wished to determine the relation between the type of change in a cell and the landscape variables, their ad hoc figure of merit would have served as a poor measure. A more acceptable measure would have been the canonical correlations between the landscape variables and the change category variables. If the matrix of categories is C, the landscape variables are Y, and the discriminant functions are A, the first canonical correlation is the multiple correlation of $u_1 = a_1 Y$ and $c_1, c_2, c_3, \ldots, c_k$, where there are k groups. The second canonical correlation is the multiple correlation of $u_2 = a_2 Y$ and $c_1, c_2, \ldots, c_k$. These statistics are calculated by the BMD07M algorithm (Dixon, 1968; Reference 19).

Most of the comments of Tom et al. comparing the maximum-likelihood classifier with the results of the BMD07M routine are specious. BMD07M uses a likelihood ratio to calculate the posterior probabilities of group membership for each sample point (Dixon, 1968; Reference 19, page 214k). This involves calculating a bilinear equation, which requires a computational effort equivalent to that of the quadratic equation used by their maximum-likelihood equation (Tom et al., 1978; Reference 18, page 203). Furthermore, BMD07M calculates Mahalanobis distance, a quadratic matrix equation. Thus, unless their description of the maximum-likelihood method used is in error, the difference in computational time discussed by Tom et al. is primarily due to the difference in efficiency of the code rather than one method being inherently more arithmetically demanding than the other.

In the BMD07M, a stepwise procedure is used to select variables that give the maximum separation between groups while minimizing the within-group variation

and the multiple correlation between each newly selected variable and those already selected.

This involves finding linear compound c, which maximizes

$$L = \frac{c' \, B \, c}{c' \, W \, c} \tag{3-1}$$

where B is the between groups, variance-covariance matrix, W is the pooled-within groups, variance-covariance matrix, and c are the eigenvectors of $W^{-1}B$, and L are the eigenvalues. If there are g groups and p variables, there are no more than min (g-1, p) positive eigenvalues in diagonal matrix L. The assignment rule is assigned to group i if (Lackenbruck, 1975; Reference 20)

$$c' \, (x - \bar{x}_i) \, (x - \bar{x}_i) \, c = \min_j \, c' \, (x - \bar{x}_j) \, (x - \bar{x}_j) \, c \tag{3-2}$$

As Lackenbruck (1975) states, the failure of assumption of common within-group variance covariances and normality causes problems.

Paraphrasing Lackenbruck's (1975) account, if f_i (x) is the probability density function for group i, then the probability of misclassifying observations of group i into group j is

$$P \, (j \mid i) = \int_{R_j} f_i \, (x) dx \quad . \tag{3-3}$$

For a particular observation x, the conditional probability of it coming from group i out of g groups is

$$P(\pi_i | x) = \frac{p_i f_i (x)}{\sum_{\ell}^{g} = p_\ell f_\ell (x)} \tag{3-4}$$

If the cost of misclassification is equal among the groups, an observation x is classified into the group i, which maximizes Equation (3-4). The problem arises when f (x) is assumed to be normal and the within-group variance-covariance matrices are assumed to be equal. As Lackenbruch (1975) points out and as Tom et al. (1978) found out, canonical analysis (BMD07M) is more robust to failure of these parametric assumptions than is maximum likelihood.

The optimal method would have been to generate empirical probability density functions with the abundant data that is generally available in image processing and to use these in a maximum-likelihood algorithm.

Acknowledging that this approach was not taken, problems remain with the manner in which the results of the canonical analysis are presented. Normally, the BMD07M algorithm uses the criteria listed above to select the variables used in the analysis; however, it is possible to force the entry of variables by using the appropriate program control cards. Tom et al. forced the Landsat variables to be the first variables included in their classification, allowing the landscape variables to enter freely thereafter. This makes it difficult to determine the optimal set of variables for discriminating between classes of cells; in trying to minimize the multiple correlation of the forced Landsat variables with the freely entering landscape variables, landscape variables that may perform better than Landsat variables but have a high multiple correlation with the Landsat variables would be excluded. Thus, forcing the Landsat variables into the classification distorts the order of entry of the landscape

variables. This can be seen by comparing Tables 20 (Landsat variables forced) and 23 (Landsat variables free) of Tom et al. (1978; Reference 18).

In Table 20, the sixth landscape variable to enter freely (the average number of year-round housing units per acre (Table 23)) is the 29th variable when the Landsat variables are forced. The second landscape variable to enter (the average number of cars per family) when the Landsat variables are forced is not included in the top seven landscape variables when Landsat variables enter freely. The same is true for the sixth landscape variable to enter (the 1969 mean family income) when the Landsat variables are forced. These results are summarized below.

Rank of Landscape Variables When Landsat Variables Enter Freely	Variable Name	Rank of Landscape Variables When Landsat Variables are Forced
1	Topographic elevation	1
Greater than 7	Average number of cars/family	2
2	Built-up urban area minimum distance	3
5	Topographic slope	4
3	Average number of families/acre	5
Greater than 7	1969 mean family income	6
7	Median housing unit value	7
6	Average number of year-round housing units/acre	29

The failure to test the redundancy between the landscape variables and the Landsat variables for the classification of the cells forced the Landsat variables into the equations and might initially cause the skeptical reader to question the need for all the forced Landsat variables.

A two-step process, in which Landsat is used to identify change cells and the landscape is used to classify them, might well be superior.

Tom et al. did correctly point out that biased results can be obtained when "typical" areas are used for training samples. A random sample of pixels from the whole image, whose ground truth is known, provides a much better method of creating training samples although it makes ground truth collection much more expensive.

SECTION 4 - MISCELLANEOUS METHODS

The discussion of differencing mentioned the work of Weismiller et al. (1977; Reference 4). In addition to using the differencing method, they used post-classification comparison to detect change. Regardless of the ability of this methodology to detect change, if fails to offer the potential economies of initially identifying change and later reclassifying only those pixels that changed. This is because both the old and new images must be completely classified. For the Census Bureau's requirements, classification (urban/nonurban) of the new image is the sole need and change detection becomes interesting only to those who wish to use the data for the further study of urban dynamics. This postclassification symbolic comparison of two dates was also used by Price and Reddy (1975; Reference 22).

Weismiller et al. (1977) also used the spectral/temporal change classification where the multitemporal image is classified and the change pixels are assumed to be clustered in a remote part of the variable space. Ellefsen et al. (1974; Reference 23) have found that multitemporal images can be broken down into a greater number of categories than monotemporal images. This not only facilitates distinguishing between urban and nonurban categories but also allows finer subcategories to be delineated.

The layered spectral/temporal method used by Weismiller et al. (1977) may provide high-quality results if the qualitative results are borne out by more quantitative studies; however, the computer resources required may prohibit its widespread usage.

SECTION 5 - SUMMARY

A variety of methods have been used for change detection but a number of these attempts have suffered from the malapropos application of statistical methods. Another serious problem has been the lack of ground truth. This has limited the ability to evaluate the success rate of the various methods used. The question of whether or not Landsat imagery can be successfully and economically used for identifying urban change is still open. None of these papers clearly address the problem of separation of error variance in pixel values from among-class variance in pixel values. An analysis of variance approach could be productive here and is being undertaken by our group.

The only methods of dimensionality reduction used have been principal components and discriminant analysis. Other linear transformations may be useful and should be investigated.

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